TEMPORAL RELATIONSHIPS AND DYNAMIC INTERACTIONS BETWEEN SPOT AND FUTURES STOCK MARKETS

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INTRODUCTION

The linkages and interactions of stock market returns and futures market returns have been an area of intense empirical investigation. Several studies find that the futures market, in general, leads the stock market, e.g., Stoll and Whaley (1990) and Kawaller, Koch, and Koch (1987). These findings are attributed to mainly two factors: First, most stocks in the index do not trade at different prices at all times, so that the index responds to new information with a lag; and, second, lower transactions costs in the futures markets make it more advantageous for investors with strong beliefs about the direction of the market to trade index futures rather than the index itself. Consequently, movements in the futures markets will lead movements in the stock market. In this respect the futures market has been described as a vehicle for price discovery in the stock market.

From the inception of futures trading in equity contracts in 1982 until 1986, Edwards (1988) finds that volatility in the stock market

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actually declined compared with the 1979–1982 period. Stock market volatility did, however, increase in 1986 and 1987. Edwards hypothesized that the initial decline in stock market volatility was due to the fact that futures trading brought more traders to the spot market, thereby, making them more liquid. Looking at a longer pre-futures market period, 1963 to 1982, Maberly, Allen, and Gilbert (1989) conclude that volatility was greater subsequent to August 20, 1982, the date futures trading was introduced, through October 16, 1987. Volatility was also greater during the post-crash period from October 20, 1987, through December 31, 1988. Overall, for the 1963 to pre-crash 1987 period, volatility was significantly greater during bear markets.

The Brady Commission's report (1988) considered the ability of the futures markets to transmit information as a cause of excess volatility in the stock market. With the futures market opening down 6.5% on the morning of October 19, 1987 [e.g., Leland and Rubinstein (1988)], it is difficult to dispute the role of the futures markets in transmitting information to the stock market. During the days preceding the October '87 crash, Gammill and Marsh (1988), in a discussion of the commission's findings, report that users of stock index futures were extremely active. Portfolio insurers, in particular, were heavy sellers in both futures and stock markets. They conclude that a breakdown in the feedback mechanisms between the two markets led to a "rational" panic. Exacerbating the problem of runaway feedback mechanisms was the ability of investors to take highly leveraged positions in the futures market.

Harris (1989) provides evidence that during the crash the two markets appeared to be disintegrated in the sense that the arbitrage mechanism became ineffective due to disruptions of the trading process. Similar findings are reported by Antoniou and Garrett (1993) for the British stock market. Bessembinder and Seguin (1992) find that futures trading activity has no impact on the volatility of the stock market. Similarly, Choi and Subrahmanyam (1994) report that the introduction of the Major Market Index (MMI) futures contract had no significant impact on the volatility of stock returns. Kupiec (1993) examines the impact of futures margin requirements on stock return volatility. Contrary to the critics' claim, he finds that higher margin rates in the futures market are associated with higher volatility in the spot market.

Despite the extensive investigation and the evidence accumulated thus far, very little has been done in terms of explicitly modeling the ways in which the two markets interact through their second moments. Most studies limit their investigation to lead/lag relationships and contemporaneous correlations. Higher moment dependencies within and across markets are largely ignored. Numerous studies however, have shown that the most important feature of speculative price changes are higher moment dependencies, e.g., Bollerslev, Chou, and Kroner (1992).

This study characterizes empirically the dynamic interdependence of the stock index and the futures index returns by taking into account both long-run equilibrium relationships (i.e., cointegration) and short-term second moment interactions. Specifically, the following questions are addressed:

i. Are the two markets linked through their second moments? Specifically, is volatility in each market influenced by developments in the other market?
ii. Is this influence asymmetric in the sense that bad news and good news in one market exert an asymmetric impact on the other market's volatility?
iii. Have there been structural changes in the coherence (correlation) of the two markets before, during and after the October '87 crash?

To answer these questions we use an error correction model with innovations following a bivariate EGARCH process to describe the joint distribution of index stock returns and index futures returns.[1] The conditional mean in each market is a function of the error correction term which imposes the long-run equilibrium relationship between the two markets. Likewise, the conditional variance in each market is an asymmetric function of own, as well as, cross-market past innovations (errors). This specification allows in-depth examination of higher moment interdependencies, i.e., volatility spillovers between markets.

The following section discusses the data used and presents several preliminary findings. The third section provides a nontechnical exposition of the bivariate error correction EGARCH model while the fourth presents and discusses the major findings.

DATA AND PRELIMINARY ANALYSIS

The data used for the spot market are daily closing prices for the S&P 500 index. Data used for the futures market are the daily settle prices for the S&P 500 futures contract traded on the Chicago Mercan-

[1]The univariate Exponential GARCH model (EGARCH) was suggested by Nelson (1991) as a means of modeling the tendency of stock market returns to be more volatile in periods following market declines.

tile Exchange (CME).[2] The delivery months for the S&P 500 futures contract are March, June, September, and December. To avoid problems associated with thin trading, observations from the most actively traded contract are used, thus creating a time-series of nonoverlapping contracts. The period of analysis extends from 1/4/84 to 12/31/93 for a total of 2770 observations.

Several studies find that, more often than not, the levels of financial time series have a unit root in their univariate representation, e.g., Doukas and Rahman (1987) and Meese and Singleton (1982). To test for unit roots in the logarithm of the futures and the index price, the augmented Dickey–Fuller test is used [see Dickey and Fuller (1979), (1981)].[3]

Table I, Panel A, reports the results for both the logarithm and the logarithmic first difference of the futures and the index price. The test statistic fails to reject the hypothesis that the log of the futures price and the index price have a unit root. This simply means that the series are not stationary, or, integrated of order one [i.e., I(1) process]. Thus, modeling the levels of these variables is meaningless. Series with unit roots, however, are difference stationary. As evident from Table I, the unit root hypothesis is decisively rejected for the returns.[4] Engle and Granger (1987) show that, if two nonstationary variables are cointegrated, then modeling of the first differences should incorporate an error correction term. The Engle–Granger statistic, reported in Table I, shows that the logarithm of the stock index and the futures contract are cointegrated, i.e., they obey a long-run relationship.[5] These findings provide a justification for using index returns and futures returns along with an error correction term in the subsequent analysis.

Table I, Panel B, reports summary statistics for daily stock index and futures percentage returns. The statistics reported are: the mean

[2]Settle price is usually the price of the closing trade of the day. If there is no trade at the close the average of the bid and ask prices is used to determine the settle price. If multiple trades occur at the close, the settle price is calculated as the average of these trades.

[3]According to the Dickey–Fuller method, testing for a unit root in a process, $\{y_t\}$, involves estimating the model

$$\Delta y_t = a_0 + a_1 t + a_2 y_{t-1} + \sum_{s=1}^{k} C_s(\Delta y)_{t-s} + u_t$$

where Δ is the first-difference operator and t is a time trend and testing the null hypothesis $H_0 : a_2 = 0$ vs., $H_1 : a_2 < 0$. Acceptance of the null hypothesis implies that a unit root is present in y_t.

[4]Testing for a unit root in the percentage change is equivalent to testing for a second unit root in the logarithm of the level variables.

[5]According to Engle and Granger (1987), two nonstationary variables, y_t and x_t, are cointegrated if there exists a linear combination, $\epsilon_t = y_t - \alpha - \beta x_t$, that is stationary. The test is carried out by testing whether ϵ_t is stationary.

TABLE I
Summary Statistics

	Log of Stock Index S_t	Log of Futures F_t	Index Returns $R_{S,t}$	Futures Returns $R_{f,t}$
	Panel A. Unit Root and Cointegration Tests			
ADF	−2.9290	−3.1271	−23.8701	−24.9751
EG	−19.2955[a]			

	Stock Index Returns ($R_{s,t}$)	Futures Returns ($R_{f,t}$)
	Panel B. Summary statistics	
Mean	0.0430[a]	0.0429
Standard deviation	1.0158	1.2441
Skewness	−4.4339[a]	−6.3578[a]
Excess Kurtosis	99.8296[a]	206.1144[a]
Kolmogorov–Smirnov[b]	0.0500[a]	0.0688[a]
Ljung–Box (12 lags)[c]	39.3402[a]	85.1700[a]
Ljung–Box (12 lags)	173.5672[a]	233.9543[a]
	Sample cross correlations	
Lag	$\rho(R_{s,t}, R_{f,t-s})$	$\rho(R^2_{s,t}, R^2_{f,t-j})$
0	0.9351	0.9859
1	0.0464	0.0852
2	−0.0750	0.1407
3	−0.0397	0.0776
4	−0.0424	0.0117
5	0.0769	0.1321

Notes: [a]Denotes significance at the 5% level. Period: 1/4/84 to 12/31/93 (2770 observations).
$R_{i,t}$ are percentage returns calculated as 100*log $(P_{i,t}/P_{i,t-1})$ for $i = s, f$. ADF and EG are the Augmented Dickey–Fuller and the Engle–Granger statistics. Critical values at the 5% level are −3.41 and −3.37, respectively.
[b]Sample critical value at the 5% level is 0.0251.
[c]Critical value at the 5% level is 21.026.

and the standard deviation; measures for skewness and kurtosis; the Kolmogorov–Smirnov, testing for normality; and the Ljung–Box (LB) statistics for 12 lags.

The means for the return series are almost identical, even though the mean for the futures is statistically insignificant due to the higher standard deviation. The skewness and kurtosis measures are highly significant indicating substantial departures from normality. Likewise, the Kolmogorov–Smirnov statistics reject the assumption of normality.[6] Rejection of normality can be partially attributed to intertemporal dependencies in the moments of the series. To test for such dependences, the Ljung–Box (LB) statistic is applied to the returns and

[6]The Kolmogorov–Smirnov statistic is calculated as $D_n = \max|F_n(r) - F_0(r)|$ where F_n is the empirical cumulative distribution of r_t and $F_0(r)$ is the postulated theoretical distribution.

the squared returns. The idea is that, if a process is i.i.d., then any linear or nonlinear transformation will also be an i.i.d. process. The LB statistics for 12 lags are significant for the returns and the squared returns, suggesting the presence of linear and nonlinear intertemporal dependencies.[7] Moreover, judging from the size of the LB statistic for the squared returns, it can be concluded that nonlinear dependencies are far more prevalent. For the index returns, linear dependencies may be due to problems associated with nonsynchronous trading. For the futures returns, the problem may be due to the daily price limits imposed by the CME.[8] Nonlinear dependencies are most likely due to conditional heteroskedasticity, i.e., the tendency of large price changes to be followed by large price changes of either sign.

As expected, the unconditional contemporaneous correlation between stock returns and futures returns is very high (0.9351). Cross-lag correlations are generally low. The corresponding cross-lag correlations for the squared returns are considerably higher suggesting the presence of cross-market volatility interactions.

THE BIVARIATE ERROR CORRECTION EGARCH MODEL

Let $R_{s,t}$ be the return on the stock market index; $R_{f,t}$ the return on the futures contract; and Ω_{t-1} the information set available at $t - 1$. The model can then be described by the following system of equations:

$$R_{s,t} = \beta_{s,0} + \beta_{s,s}(S_{t-1} - \delta F_{t-1}) + \epsilon_{s,t} \tag{1}$$

$$R_{f,t} = \beta_{f,0} + \beta_{f,f}(S_{t-1} - \delta F_{t-1}) + \epsilon_{f,t} \tag{2}$$

$$\sigma^2_{s,t} = \exp\{\alpha_{s,0} + \alpha_{s,s}g_s(\xi_{s,t-1}) + \alpha_{s,f}g_f(\xi_{f,t-1}) + y_s \log(\sigma^2_{s,t-1})\} \tag{3}$$

$$\sigma^2_{f,t} = \exp\{\alpha_{f,0} + \alpha_{f,f}g_f(\xi_{f,t-1}) + \alpha_{f,s}g_x(\xi_{s,t-1}) + y_f \log(\sigma^2_{f,t-1})\} \tag{4}$$

$$gs(\xi_{s,t-1}) = (|\xi_{s,t-1}| - E|\xi_{s,t-1}|) + \theta_s\xi_{s,t-1} \tag{5}$$

$$g_f(\xi_{f,t-1}) = (|\xi_{f,t-1}| - E|\xi_{f,t-1}|) + \theta_f\xi_{f,t-1} \tag{6}$$

$$\sigma_{i,j,t} = (\rho_1 D_{1,t} + \rho_2 D_{2,t} + \rho_3 D_{3,t})(\sigma_{s,t}\sigma_{f,t}) \tag{7}$$

where, $\epsilon_{i,t}$ is the innovation (error term) at time, t; $\sigma^2_{i,t} = \mathrm{Var}(\epsilon_{i,t}|\Omega_{t-1})$ is the conditional variance; $\xi_{i,t} = \epsilon_{i,t}/\sigma_{i,t}$ is the standardized innovation; and $\sigma_{i,j,t} = \mathrm{Cov}(\epsilon_{i,t}, \epsilon_{j,t}|\Omega_{t-1})$ is the conditional covariance for $i, j =$

[7]The Ljung–Box statistic for N lags is calculated as $\mathrm{LB}(N) = T(T + 2)\sum_{j=1}^{N}(\rho_j^2/T - j)$ where ρ_j is the sample autocorrelation for j lags and T is the sample size.

[8]For the S&P 500 Futures, the minimum price movement is .05 index points, or $25 per contract.

s, f (s = stock return, f = futures return). Equations (1) and (2) model the conditional means of the stock returns and the futures returns, respectively. The term $(S_{t-1} - \delta F_{t-1})$ is the error correction term imposing the long-run equilibrium in the two markets where, S_t is the log of the stock price index and F_t is the log of the futures price. The cointegrating parameter, δ, is equal to one in the regression used to test for cointegration. Since this estimate is super consistent, the restriction, $\delta = 1$, is imposed on eqs. (1), (2) in the remainder of the analysis.[9]

The conditional variance in each market [eqs. (3) and (4)] is an exponential function of past own, as well as, cross-market standardized innovations. The particular functional forms for g_s and g_f are given in (5) and (6). As can be seen, $g_i(\cdot)$ is an asymmetric function of past standardized residuals for $i = s, f$. For $-\infty < \xi_{i,t-1} < 0$, the slope of $g_i(\cdot)$ is equal to $-1 + \theta_i$. For $0 \leq \xi_{i,t-1} < +\infty$, the slope becomes $1 + \theta_i$. Thus, eqs. (5) and (6) permit standardized innovations to influence the conditional variances asymmetrically. More intuitively, the term $|\xi_{i,t-1}| - E|\xi_{i,t-1}|$, measures the magnitude effect; whereas, the term, $\theta_i \xi_{i,t-1}$, measures the sign effect. Depending on the sign of coefficients, $\alpha_{i,i}$ and θ_i, the sign effect may reinforce or partially offset the magnitude effect. For example, a negative innovation ($\xi_{i,t} < 0$) will be followed by higher volatility than a positive innovation ($\xi_{i,t} > 0$) if $\alpha_{i,i} > 0$ and $-1 < \theta_i < 0$. Such a response would be consistent with the leverage effect that has been observed in the stock market, whereby market declines produce a higher aggregate debt to equity ratio and, hence, higher volatility, e.g., Black (1976), Christie (1982), and Nelson (1991), among others. In terms of cross-market volatility spillovers, a declining futures market ($\xi_{f,t} < 0$) will be followed by higher stock market volatility than a futures advance if $\alpha_{s,f} > 0$ and $-1 < \theta_f < 0$. Similarly, volatility spillovers from the stock to the futures market will be more pronounced during stock market declines if $\alpha_{f,s} > 0$ and $-1 < \theta_s < 0$.

The contemporaneous relationship between $R_{s,t}$ and $R_{f,t}$ is captured by the conditional covariance specification, given by (7). This specification is similar to Bollerslev (1990) with a small difference. The difference is due to the terms, $\rho_1 D_{1,t}, \rho_2 D_{2,t}$, and $\rho_3 D_{3,t}$, that test for structural changes in the contemporaneous relationship between $\epsilon_{s,t}$ and

[9]Note that the formula used for futures pricing [see MacKinlay and Ramaswamy (1988)]

$$F_{t,T} = S_t \exp(r - d)(T - t)$$

where F_t, S_t, r, d, T are the futures price, the spot price, the risk-free rate, the dividend yield and the time to expiration respectively, also implies a unitary cointegrating coefficient.

$\epsilon_{f,t}$. $D_{1,t}$ is a dummy for the pre-crash period (1/3/83–9/30/87), $D_{2,t}$ is a dummy for the crash period (10/1/87–10/30/87), and $D_{3,t}$ is a dummy for the post-crash period (11/2/87–12/31/93). If $\rho_1 = \rho_2 = \rho_3$, then it can be concluded that no structural change has occurred over the sample period and the constant correlation assumption is appropriate. Note that constant correlation implies that the covariance, $\sigma_{s,f,t}$, is proportional to the product of the standard deviations. This may appear to be too restrictive, but it is implied in futures pricing models such as the cost-of-carry model. This model, in fact, predicts the correlation of the returns of the two markets will be constant and equal to unity [see Stoll and Whaley (1990)].[10] Assuming that the conditional joint distribution of $R_{s,t}$ and $R_{f,t}$ is normal, the log likelihood for the bivariate EGARCH model can be written as,

$$L(\Theta) = -T \log (2\pi) - (1/2) \sum_{t=1}^{T} (\log |S_t| + \epsilon_t S_t^{-1} \epsilon_t') \tag{8}$$

where, Θ is the parameter vector to be estimated; $\epsilon_t = [\epsilon_{s,t} \epsilon_{f,t}]$ is the 1×2 vector of innovations at time, t; S_t is the 2×2 time varying conditional variance–covariance matrix with diagonal elements given by (3) and (4); and cross-diagonal elements are given by (7). The log-likelihood function is highly nonlinear in Θ and, therefore, numerical maximization techniques have to be used. The Berndt, Hall, Hall, and Hausman (1974) algorithm which utilizes numerical derivatives to maximize $L(\Theta)$ is used here.

EMPIRICAL FINDINGS AND DISCUSSION

The bivariate EGARCH model is estimated by imposing two restrictions, namely, (i) all cross-market volatility spillovers are zero ($\alpha_{s,f} = \alpha_{f,s} = 0$) and (ii) the correlation coefficient is constant ($\rho_1 = \rho_2 = \rho_3 = \rho$). The purpose of this exercise is twofold: first, to establish a benchmark against which comparisons can be made; and, second, to document any changes in the coefficients describing the conditional mean and variance due to volatility interactions between the two markets, as well as, changes in the correlation structure.

Table II reports the results on the benchmark (restricted) bivariate EGARCH model. Parameters, $\beta_{s,s}$ and $\beta_{f,f}$ are statistically significant at the 5% level; therefore, the error correction term is an important determinant of the conditional means of the stock and futures returns. Recent studies dealing with the short-term dynamics of currency markets

[10]Perfect correlation also requires that dividend yields and interest rates are nonstochastic.

TABLE II
Maximum Likelihood Estimates for the Benchmark Model

Coefficient	$R_{s,t}$	*Coefficient*	$R_{f,t}$
$\beta_{s,0}$	0.0259	$\beta_{f,0}$	0.0193
	(0.0148)		(0.0160)
$\beta_{s,s}$	−0.0241	$\beta_{f,s}$	0.0701
	(0.0099)[a]		(0.0105)[a]
$\alpha_{s,0}$	−0.0429	$\alpha_{f,0}$	0.0203
	(0.0066)[a]		(0.0045)[a]
$\alpha_{s,s}$	0.2562	$\alpha_{f,f}$	0.2623
	(0.0098)[a]		(0.0102)[a]
θ_s	−0.2347	θ_f	−0.4051
	(0.0391)[a]		(0.0365)[a]
γ_s	0.7575	γ_s	0.7955
	(0.0079)[a]		(0.0019)[a]
$\rho_{s,f}$	0.9284		
	(0.0018)[a]		
HL	2.4956		3.0295
Model diagnostics			
$E(\epsilon_t/\sigma_t)$	0.0205		0.0224
$E(\epsilon_t/\sigma_t)^2$	1.0193		1.0103
LB(12)[b] for (ϵ_t/σ_t)	15.4219		6.7742
LB(12) for $(\epsilon_t/\sigma_t)^2$	4.5939		3.6037

Notes: [a]Denotes significance at the 5% level. Period: 1/4/84 to 12/31/93 (2770 observations).
Numbers in parentheses are asymptotic standard errors.
[b]LB(12) is the Ljung–Box statistic for 12 lags; critical value at the 5% level is 21.026.
HL is the half life of an innovation calculated as $\log(0.5)/\log(\gamma_i)$ for $i = s, f$.

report similar findings, e.g., Kroner and Sultan (1993) and Sultan (1994). Volatility in both markets is an asymmetric function of past standardized residuals. In this respect, the coefficients, $\alpha_{s,s}$ and $\alpha_{f,f}$, are positive and statistically significant; whereas, the coefficients, θ_s and θ_f, which measure the sign effect, are negative and statistically significant. This result implies that negative returns (market declines) are followed by higher volatility than positive returns (market advances) of an equal magnitude. On the basis of the estimated coefficients, a negative innovation in the stock market will increase volatility by 1.61 times more than a positive innovation of an equal magnitude. This phenomenon is attributed to the leverage effect that was mentioned earlier. For the futures market, the degree of asymmetry is much higher, i.e., a negative innovation increases volatility 2.36 times more than a positive innovation.[11] There is no obvious explanation as to why futures return volatility responds asymmetrically to past innovations. The leverage effect argument used for the spot market clearly does not apply to the futures market. One possible explanation is that the leverage of the

[11]The degree of asymmetry, leverage effect, is measured by the ratio, $|-1 + \theta_i|/1 + \theta_i$ for $i = s, f$.

individual investor rises following a futures market decline or that the market sentiment reacts more to bad news. Further research is needed to determine the underlying causes.

The degree of volatility persistence is high in both markets, judging from the size of γ_s and γ_f. Based on the estimated coefficients, the half-life (HL) of a shock on volatility is 2.4956 days for the stock market and 3.0295 days for the futures market. These estimates are important for forecasts of future volatility. The diagnostics of the restricted model show that the standardized residuals have zero means and unit variances, and they are linearly and nonlinearly independent.

The maximum likelihood estimates of the unrestricted bivariate EGARCH model are reported in Table III. The error correction term is again statistically significant implying that omitting this term would lead to model misspecification. Furthermore, the role of this term could be interpreted in more practical terms. Analysts believe that the basis (i.e., futures price minus index price) will tend to be positively related to future stock returns. This is consistent with the notion that

TABLE III
Maximum Likelihood Estimates for the Unrestricted EGARCH Model

Coefficient		$R_{s,t}$		*Coefficient*		$R_{f,t}$
$\beta_{s,0}$		0.0276 (0.0165)		$\beta_{f,0}$		0.0167 (0.0181)
$\beta_{s,s}$		−0.0516 (0.0099)[a]		$\beta_{f,f}$		0.0299 (0.0107)[a]
$\alpha_{s,0}$		−0.0434 (0.0085)[a]		$\alpha_{f,0}$		0.0255 (0.0059)[a]
$\alpha_{s,s}$		0.1668 (0.0096)[a]		$\alpha_{f,f}$		0.1435 (0.0083)[a]
$\alpha_{s,f}$		0.1480 (0.0066)[a]		$\alpha_{f,s}$		0.0015 (0.0083)
θ_s		−0.1303 (0.0191)[a]		θ_f		−0.2403 (0.0209)[a]
γ_s		0.6879 (0.0102)[a]		γ_S		0.7429 (0.0121)[a]
ρ_1	0.9279 (0.0025)[a]	ρ_2	0.8790 (0.0461)[a]	ρ_3	0.9396 (0.0018)[a]	
HL		1.2996				1.6326
Model diagnostics						
$E(\epsilon_t/\sigma_t)$		0.0176				0.0194
$E(\epsilon_t/\sigma_t)^2$		0.9992				1.0034
LB(12)[b] for (ϵ_t/σ_t)		14.6128				8.1534
LB(12) for $(\epsilon_t/\sigma_t)^2$		11.6124				4.8467

Notes: [a]Denotes significance at the 5% level. Period: 1/4/84 to 12/31/93 (2770 observations).
Numbers in parentheses are asymptotic standard errors.
[b]LB(12) is the Ljung–Box statistic for 12 lags; critical value at the 5% level is 21.026.
HL is the half life of an innovation calculated as $\log(0.5)/\log(\gamma_i)$ for $i = s, f$.

new market information will impact the futures market first. Thus, a large basis would indicate an impending bullish stock market [see also Kawaller, Koch, and Koch (1987)]. Note that the error correction term is essentially the basis multiplied by -1. The fact that this term is significantly negatively related to stock returns implies that the basis can be used as an indicator of future stock movements.

The conditional variance in both markets is again predictable on the basis of past innovations. As is the case with the restricted model, the impact of these innovations is asymmetric. Focusing on second moment cross-market interactions, it can be seen that the conditional variance of stock returns is a function of own past innovations (coefficient $\alpha_{s,s}$), as well as, past innovations generated by the futures market (coefficient $\alpha_{s,f}$). Interestingly, these volatility spillovers are asymmetric, in the sense that bad news (negative innovations) in the futures market increases volatility in the stock market more than good news (positive innovations). For example, the contribution of a negative futures market innovation to the volatility of the stock market is proportional to $\alpha_{s,f} + \alpha_{s,f}\theta_{f,f}$; whereas, the contribution of a positive innovation is proportional to $\alpha_{s,f} - \alpha_{s,f}\theta_{f,f}$. The estimates for these coefficients indicate that a given futures market decline increases volatility in the stock market 1.6326 times more than a futures market advance of an equal magnitude. This asymmetric response can be explained on the grounds that the futures market leads the spot market so that a futures decline will, on average, be followed by a decline in the spot market. This impending decline leads to an expected higher debt to equity ratio and, thus, to higher volatility in the spot market.

Turning to the futures market, the evidence shows that there are no significant volatility spillovers from the stock to the futures market. The coefficient measuring volatility spillovers from the stock to the futures market, $\alpha_{f,s}$, is statistically and economically insignificant. Thus, information from the futures market can be used to predict the volatility in the stock market but not vice versa. This appears to be in agreement with the findings of Stoll and Whaley (1990); Harris (1989); and Kawaller, Koch, and Koch (1987) even though these studies examine primarily first moment lead/lag relationships.[12]

[12]Chan, Chan, and Karolyi (1991) use a multivariate GARCH model to test second moment interactions in the stock and futures markets. Their findings suggest that innovations from the futures market affect the volatility in the stock market and vice versa; whereas, this study finds a one way causation from the futures to the stock market. The difference may be due to different sample periods and frequencies (they use intraday data from 1984 to 1989) or, to methodological differences.

The contemporaneous relationship between the two markets is, perhaps, the most important one. As mentioned earlier, the cost-of-carry model, linking the price of the index futures contract and the price of the stock index, predicts, among other things, that the contemporaneous rates of return in the two markets should be perfectly correlated. The estimated correlation coefficients for the pre-crash, during crash, and post-crash periods are 0.9279, 0.8790, and 0.9396, respectively. It is interesting to note the decline in the correlation (coherence) of the two markets during the month of October, 1987. Studies using intraday data find a more pronounced decoupling of the two markets during the day of the crash, e.g., Harris (1989). For the post-crash period, the estimated correlation coefficient is almost identical to that estimated for the pre-crash. A simple t-test fails to reject the hypothesis that $\rho_1 = \rho_3$. Thus, whatever the cause of the disintegration of the two markets in October, 1987, the linkages were re-established shortly thereafter. The stability of the correlation coefficient, however, does not imply stability of the covariance structure of the returns of the two markets. As can be seen from eq. (7), the conditional covariance is time varying since the conditional standard deviations are time varying. This is important for hedging purposes because conventional hedging techniques assume a constant covariance structure. Dynamic hedging, on the other hand, would take advantage of the time varying nature of the covariance. Kroner and Sultan (1993) find that dynamic hedging in currency markets leads to superior risk reduction than conventional hedging, even when transactions costs are considered.

The hypothesis that the pre- and post-crash correlations are unity is rejected on the basis of a t-test. It may be that the assumptions required for perfect correlation, i.e., nonstochastic interest rates and dividend yields, are too restrictive.

At this point it is useful to compare the coefficients obtained under the assumption of no interaction and constant correlation (Table II) to those obtained when interaction and changes in the correlation structure are allowed (Table III). The coefficients, $\alpha_{s,s}$ and $\alpha_{f,f}$, linking the conditional variance to the asymmetric functions, $g_s(\cdot)$ and $g_f(\cdot)$, respectively, are considerably lower in the unrestricted model. The same holds true for the coefficients that measure the degree of asymmetry, θ_s and θ_f. Thus, the leverage effect in the stock market can partially be attributed to asymmetric volatility spillovers from the futures market. Likewise, the persistence of volatility, measured by γ_s and γ_f, is also reduced. In terms of the half-life of a shock, it is now 1.2996 days for the stock market and 1.6326 for the futures market. This reduction in persistence supports the claim that volatility persistence may be due to omitted variables, e.g., Lastrapes (1989).

The restricted is tested against the unrestricted model using the likelihood ratio (LR) statistic (i.e., $H_0 : \alpha_{s,f} = \alpha_{f,s} = 0$ and $\rho_1 = \rho_2 = \rho_3 = \rho$). This statistic is distributed as χ^2 with degrees of freedom equal to the number of restrictions (five in this case). The calculated statistic is 137.9827, thus, rejecting the null hypothesis at almost any level of significance. The importance of this finding is that equilibrium models that rely exclusively on contemporaneous relationships and neglect second moment interactions may be misspecified.

Diagnostics based on the standardized residuals of the bivariate EGARCH model confirm that they have zero mean and unit variance, as expected. Furthermore, on the basis of the Ljung–Box test, they are linearly and nonlinearly independent. Overall, the model successfully captures contemporaneous relationships as well as cross-market second moment interactions. The constant correlation specification, modified to account for structural shifts, appears to be a reasonable parameterization of the covariance of the returns of the two markets.

SUMMARY AND CONCLUDING REMARKS

This study models the joint distribution of stock index returns and futures index stock returns using a bivariate error correction EGARCH model. This model describes short-term dynamics while preserving the long-run equilibrium relationship linking the two markets. Daily volatility in both markets is highly persistent and predictable on the basis of past innovations. In agreement with earlier studies for the U.S. stock market, stock return volatility is found to be an asymmetric function of past innovations, named the leverage effect. A similar pattern is found in the volatility of futures returns. In fact, the degree of asymmetry is much higher in the volatility of futures returns. These findings indicate that short-term dynamics in the two markets are very similar. More importantly, innovations originating in the futures markets increase volatility in the stock market in an asymmetric fashion, i.e., bad news increases volatility more than good news. Innovations in the stock market have no impact in the volatility of the futures market. There is evidence that the leverage effect in the S&P 500 index is reduced when spillovers from the futures market are accounted for.

The correlation of the returns of the two markets declined during the period surrounding the October, 1987 crash. The decline however, was short lived. Thus, with the exception of October, 1987, the correlation structure of the two markets appears to be remarkably stable despite the regulatory changes initiated subsequent to the crash.

Overall, the findings of this study suggest that equilibrium models that rely exclusively on contemporaneous relationships may be misspecified. Likewise, hedging strategies that ignore the time varying covariance structure of the two markets are likely to be less than optimal.

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